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Integrated Framework for Assessing Green Efficiency in European Union Countries: A Hybrid ISM-NDEA Approach

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Abstract

Environmental sustainability has become a primary concern for businesses and policymakers aiming to balance economic growth with ecological preservation. This urgency is driven by the increasing pressures of climate change, resource depletion, and heightened societal expectations for sustainable practices. Recognizing the need for a method to assess environmental and economic efficiency, this study introduces an innovative hybrid approach that combines Interpretive Structural Modeling (ISM) with Network Data Envelopment Analysis (NDEA), offering a refined framework for measuring green efficiency that addresses both environmental and economic dimensions. This methodology leverages expert insights to pinpoint and organize key variables affecting green efficiency, employing ISM to construct a comprehensive model. The ISM-structured model informs the selection of a suitable DEA variant (either simple or network) and elucidates the role of each variable as an input, intermediate process, or output measure. Subsequently, green efficiency values are calculated using the DEA model identified by ISM. This approach is then applied to calculate the green efficiency of European Union (EU) countries, providing a benchmark for measuring green efficiency across the EU. Our analysis uncovers significant findings that highlight disparities in green efficiency among EU members, revealing areas for policy improvement and resource allocation. The insights gleaned from this study have implications for stakeholders seeking to enhance their operational sustainability, providing a roadmap for better-informed and more effective policy and business strategies aimed at fostering sustainable development.

Keywords: Environmental and economic efficiency, European union countries, Green efficiency, Interpretive structural modeling, Network data envelopment analysis, Sustainability.

1 | Introduction

In recent years, the rapid expansion of industry and globalization has brought forth substantial economic opportunities for countries worldwide, including those within the European Union (EU). However, positive

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economic growth has come with growing concerns regarding escalating environmental degradation, which has raised alarms among governments, international bodies, and the general public [1]. Over the past decade, the EU has actively engaged in efforts and commitments to prioritize environmental protection, reduce pollution, and advance sustainable development goals [2]. Addressing climate change has become a central focus for both the EU and its member states [3]. The EU's recognition of environmental concerns has prompted a heightened focus on the urgent need to reduce the ecological impact of human activities [4]. This commitment is evident in initiatives such as the Europe 2020 Strategy, the Climate and Energy Plans 2030, and the Europe 2050 Vision, aimed at fostering a sustainable, competitive, and healthy environment. Neglecting these issues may lead to adverse environmental effects, which can constrain the growth potential of industries and hinder future economic development [5].

Conversely, the long-term enforcement of environmental regulations significantly affects both economic growth and environmental conservation efforts. On the other hand, economic efficiency is considered a crucial factor for sustainable development in EU countries [6]. He Europe 2020 strategies have been formulated to transform the EU into a stable and advanced economy with a high level of economic efficiency, while strengthening its position as a key player in global governance. Therefore, addressing environmental concerns, including adopting green efficiency through environmental-economic efficiency, becomes indispensable for fostering economic growth. Despite awareness of pollution and environmental issues, the progress made towards sustainable development has not met expectations and is deemed inadequate.

As a result, addressing environmental damage prevention while enhancing economic efficiency has taken center stage in the EU agenda. Given these developments, significant questions emerge regarding whether EU countries are efficient. Various methods for evaluating green efficiency have been introduced, including Data Envelopment Analysis (DEA), which is a widespread technique for measuring the efficiency of Decision-Making Units (DMUs). The primary advantage of this method is its applicability in evaluating the efficiency of any DMU that uses inputs to produce outputs. Many different DEA models are used in surveys of economic, social, and environmental evaluations to achieve reliable results [7].

However, conventional approaches such as classical DEA in evaluating DMUs have limitations that may lead to inaccurate results. Determining the suitable model type (simple or network) and ascertaining the role of variables within DEA models is particularly challenging, especially when dealing with multistage systems and a large number of variables. Consequently, introducing new and innovative approaches to address these challenges is of significant interest. To address the need for green efficiency to encompass both economic benefits and environmental protection, this study proposes an innovative framework for its evaluation. This framework considers economic efficiency and environmental efficiency as integral components in assessing green efficiency. In this study, the integration of Interpretive Structural Modeling (ISM) and the DEA method is used to evaluate green efficiency in EU countries. This integration offers a pioneering approach where ISM helps determine the appropriate structure of the DEA model (whether classical or network) and highlights the role of variables as inputs, intermediaries, or outputs within the model. This combined methodology enables a more comprehensive assessment of green performance while considering the network relationships between variables. Key contributions of this study include:

I. Introducing, for the first time, the integration of ISM and DEA as a pioneering approach for assessing green efficiency and demonstrating its application through a case study.

II. Proposing an innovative application of the ISM model to determine the appropriate structure of the DEA model and identify the role of variables within that structure.

III. Identifying the competitive advantage of economic DMUs through sensitivity analysis.

In light of the aforementioned considerations, this study introduces a new approach, called DEA-based on ISM, to evaluate the green efficiency of EU countries. This integrated methodology not only facilitates future research on green development but also provides policymakers and stakeholders with a valuable tool for evaluating and monitoring green performance. Furthermore, inspired by Cook et al.'s [8] model, we provide

a model to adapt to undesirable variables to draw a more complete picture of green performance. Additionally, the implementation of sensitivity analysis allows for the evaluation of the impact of input indicators on Gross Domestic Product (GDP). This allows for the strategic utilization of natural resources and the enhancement of production efficiency, ultimately leading to an increase in GDP.

The subsequent sections of this study are structured as follows. Section 2 offers a review of related literature. The proposed method, ISM-based Network DEA, is then presented in Section 3. An empirical study is outlined in Section 4. Finally, the last section encompasses a discussion of the findings and concluding remarks.

2|Literature Review

This section provides a review of the literature on the techniques employed in the study.

2.1|Interpretive Structural Modeling

The ISM methodology, first proposed by Warfield [9], represents a comprehensive approach developed by integrating discrete mathematics, graph theory, group decision-making, and computer science This methodology simplifies the complexities of the relationships between elements within a subject or system, allowing for the understanding and mapping of relationships among multiple factors in a complex structure [10]. ISM is an interactive learning process that organizes a set of interrelated elements into a comprehensive systematic model [11]. A fundamental logical principle of this method is that elements exerting a greater impact on other elements within the system hold greater importance [12]. The model derived from this methodology effectively illustrates the structure of complex problems, topics, systems, or fields of study [13]. To date, numerous studies have successfully used this method to identify influencing variables and structure problems, subjects, systems, or complex areas of study. *Table 1* showcases several of these instances. Additionally, Moradi et al. have presented an innovative model of this method to generate exogenous weights for dynamic network structures [14]. In this study, for the first time, this method is employed to determine the type of DEA model structure (classic or network) and to ascertain the role of variables such as inputs, intermediaries, and outputs.

Table 1. A review of the research conducted.

Sharma et al. [15]	Identifying and structuring the most influential factors driving building managers to adopt energy conservation measures for the benefit of society.	Top management supports and commitment, advance technology, government compliance and policies, performance measurement system, green logistic system, customer awareness, GSCM based strategic planning, green organization culture, green purchasing, and green packaging, team work and employee motivation, sustainable business practices, green policies and infrastructure, reducing energy consumption, waste management system, environment green subsidies, resource planning, customer's green product demand, green process and product design, competitive global strategy, training and education concern to environment, management of hazardous waste material and pollution prevention, GSCM based working environment, stakeholder pressure, corporate social responsibility/ NGO's demand and green auditing, sustainable environment, green supplier and development, penalty, collaboration and cooperation in GSCM system

Table 1. Continued.

Author	Objective	Variables
Chakraborty [16]	Identifying the internal factors of green supply chain management practices and developing a conceptual model to classify these factors into different clusters based on their driving power and dependence. Additionally, identifying a green supply chain implementation strategy from a managerial perspective.	Top management commitment, Supplier development, Raw materials and management, Logistics system, Pollution prevention and hazardous waste management, Reverse logistic management, environmentally friendly packaging, Application of advance technology and IT tools
Sarkar et al. [17]	Presenting a structured model of drivers for adopting green business when emerging economies	Customer's demand, supplier demand, cost efficiency, green image, laws and regulations, inducements, competitive advancement, global environmental pressures and public awareness, technological advancement, recourses, stakeholder/investors' pressure, executives innovativeness
Yanga and Lin [18]	Creating a conceptual framework for implementing green innovation that considers the impact of influential factors and contributes to understanding how these factors interact and affect green innovation performance.	Top management commitment, economic benefits, corporate social responsibility, employees' education and training , technological capabilities, employees' involvement and incentives, implementing an environmental quality management system, environmental regulations social recognition, market competition, market competition, guidance and support from regulatory authorities, consumer demands, long-term relationships with supply chain partners, trust relationships with supply chain partners, supervision of supplier performance, supplier incentive system, information and knowledge sharing with supply chain partners
Azevedo et al. [19]	Establishing the causal and hierarchical relationships among the variables linked with the adversities and limitations of biofuel production from biomass, and their impact on the sustainability of countries' biomass resources.	Adversities and constraints associated with the production of bioenergy from biomass, more efficiency in harvesting, processing, and transportation infrastructure, high energy production costs, high costs of biomass, positive impacts on countries' sustainability, reducing dependence on fossil fuels, reducing greenhouse gas emissions, supporting new investments, driving job creation and fixing in rural regions, driving innovation and new emerging technologies, revitalizing rural regions, promoting forest management, consolidating renewable energy consumption, allowing projects feasibility for investors, valuing by-products and residues
Handa et al. [20]	Developing a structural model and identifying and prioritizing the drivers influencing the implementation of green manufacturing	Regulatory compliance pressure, impetus of investors, eco innovations, competitor pressure, need for resource conservation, waste disposal, suppliers awareness, financial incentives, consumers pull for greener products, employees welfare
Panigrahi and Sahu [21]	Analyzing and structuring the influential variables and examining the interactions among the enablers of green supply chain management.	Complying with environmental standards, green methods to reduce the solid waste, green methods to reduce GHG emissions, avoiding noise pollution, using eco-friendly raw materials, use of green technology to make savings, utilizing the waste from other companies, recycling of intra-company material, implementing remanufacturing, green supplier selection, recovery of end-of-life products, urging suppliers to take environmental action, green packaging, motivating customers about green products

Table 1. Continued.

Author	Objective	Variables
Ghorbanpoor et al. [22]	Presenting a structural model for green supply chain management measures	Legal requirements and regulations, communication and interaction with stakeholders, financial and investment improvement, green production and operations, green procurement and supply, green design, energy consumption and resources management, waste management, indoor environment management, greenhouse gas management, management External environment, education, research and green culture, reverse logistics, warehousing, green transportation and distribution, technology, and green technology
Diabat and Govindan [23]	Identifying and prioritize the key factors that influence the implementation of a green supply chain and to analyze the interrelationships among these identified drivers	Certification of suppliers' environmental management system, environmental collaboration with suppliers, collaboration between product designers and suppliers to reduce and eliminate product environmental impacts, government regulation and legislation, green design, ISO 14001 certification, integrating quality environmental management into planning and operation process, reducing energy consumption, reusing and recycling materials and packaging, environmental collaboration with customers, reverse logistics
Amrina and Vilsi [24]	Structuring and analyzing the relationships among the Key Performance Indicators for evaluating sustainable manufacturing in the cement industry.	Material cost, energy consumption, inventory cost, occupational health and safety, fuel consumption, labor cost, accident rate, training and education, product delivery, raw material substitution, air emission, labor relationship, material consumption, employee involvement, noise pollution, gender equity, land utilization, nonproduct output
Amrina and Yusof [25]	Structuring and analyzing the interrelationships among the key performance indicators for evaluating sustainable manufacturing in the automotive industry.	Emission, resource utilization, waste, quality, cost, delivery, flexibility, labor, supplier

2.2 | Network DEA

The Network Data Envelopment Analysis (NDEA) models have emerged as comprehensive extensions of classical DEA models, aiming to provide a holistic approach to measuring the efficiency of DMUs within a network context [26], [27]. These models incorporate interrelationships among DMUs to enhance their applicability in specific managerial settings [26]. By considering these interrelationships, NDEA models offer valuable insights into resource allocation inefficiencies, guiding managers in enhancing the efficiency of their DMUs [28]. Contrary to hierarchical structures, NDEA models adopt a network-based framework to organize activities. In this framework, each DMU consists of two or multiple sub-DMUs, where the output of each sub-DMU is used as input for the subsequent sub-DMU until the final sub-DMU generates the ultimate output [29]. This network structure allows for a more comprehensive analysis of efficiency, considering the interdependencies and flows among DMUs within the network [30]. Considering that the selection of inputs and outputs is a key focus in NDEA literature, NDEA models include a wide range of input and output types. These include:

I. Initial inputs, which are allocated to the first stage.

II. Undesirable outputs, which are not utilized in any of the stages.

III. Intermediate outputs, generated in one stage and utilized in subsequent stages.

IV. Desirable outputs, produced in one stage but not utilized in subsequent stages [8].

Hence, it is imperative for this study to introduce a model that encompasses all potential input and output modes. *Table 2* presents a concise summary of the research literature pertaining to the field under investigation.

Table 2. List of identified variables in recent literature.

Author	Title	Input	Intermediate	Output
Djordjević et al. [31]	Environmental efficiency assessment of Dublin Port using two-stage non-radial DEA model	Total number of terminals, capital expenditure, vessels arrived	Goods received, goods forwarded, energy consumed per ton of volume throughput	Total number of vehicles/trucks, operating profit, total emissions produced per yr
Yang et al. [32]	Sustainability performance analysis of environment innovation systems using a two-stage network DEA model with shared resources	Expenditure on R&D, R&D full-time equivalent, Electricity	Green patent applications	New products, GDP, carbon emissions
Mehmood et al. [33]	Spatio-temporal differentiation mode and threshold effect of Yangtze River delta urban ecological well-being performance based on network DEA	Labor force, gross capital, total population	GDP	CO2 emissions, high income, low income
Ouyang and Yang [34]	The network energy and environment efficiency analysis of 27 OECD countries: A multiplicative network DEA model	Income, population, government spending, oil, coal, land	Labor, energy, inferotemporal, investment	Consumption, GDP, HDI, CO2,
Chen et al. [35]	A two-stage NDEA approach for measuring and decomposing environmental efficiency	Number of industrial employed persons, total industrial investment in fixed assets, total energy consumption by industry, annual expenditure of industrial waste water treatment facilities, investment completed in the treatment of waste water	Industrial waste water treated, gross industrial product	Total volume of chemical oxygen demand discharged by industry
Iftikhar et al. [36]	Energy and CO2 emissions efficiency of major economies: A network DEA approach	Labor, capital, energy, CO2 emissions	GDP	Population, MI, HI, LI
Li et al. [37]	An evaluation of the impact of environmental regulation on the efficiency of technology innovation using the combined DEA model: a case study of Xi'an, China	R&D staff full-time equivalent, R&D capital stock, environmental regulation, government support	Number of patent applications	New product sales revenue, technology market maturity, environmental pollution index

2.3 | Treating Undesirable Outputs in DEA

In DEA, the criterion for unit efficiency is achieving more output with less input. However, it is important to acknowledge that DMUs may not always aim to increase output and decrease input, as outputs and inputs can be either favorable or unfavorable. In such circumstances, enhancing the performance of DMUs can be achieved by increasing the production of desirable output and reducing the production of undesirable output, while also minimizing input consumption. Several approaches have been proposed in the literature to handle undesirable outputs within the DEA framework, delineated herein as direct and indirect techniques. Direct methods in DEA maintain the original values of undesirable outputs while altering the underlying assumptions governing the technology set. Some direct approaches include the following: hyperbolic methods [38], directional output distance function [39, 40], models such as Undesirable Output (UO), Input-Undesirable Output (IUO), Normalized Undesirable Output (NUO) models [41] assuming a weak feasibility principle, treating undesirable outputs as inputs, the INP method assuming a strong feasibility principle [42], and Young's method [43], which considers both weak and strong feasibility principles. In contrast, indirect approaches change the original undesirable output values through the application of a strictly decreasing function. Some indirect approaches can also be categorized into the additive inverse method [44], the linear transformation (TRβ) method [42], and the multiplicative inverse method.

Based on the aforementioned content, it can be concluded that the literature on managing undesirable outputs in DEA is extensive and diverse, encompassing a range of methods and approaches aimed at enhancing the effectiveness and practical application of DEA models in real-world contexts [45]. Despite this diversity, researchers in this field have not yet reached a theoretical conclusion. In this study, a prevalent approach involving treating undesirable outputs as inputs of the same nature has been employed.

2.4 | Research Gaps in Literature

Despite the increasing interest in measuring green efficiency, there remains a significant gap in the literature regarding a comprehensive and coherent framework for evaluating and comparing the efficiency values of DMUs, particularly within EU countries. From 2015 to 2022, research on the concept of green efficiency has been limited, with a majority of studies focusing on China. Furthermore, there is a notable lack of research on green efficiency within EU countries despite their status as pioneers in sustainable development and research. Most studies in this area have only assessed economic efficiency, neglecting the importance of environmental efficiency. The existing literature often focuses on either the ISM or DEA model approaches, but not both. Most of the research in this field primarily uses DEA as an independent method to evaluate green efficiency. Although this approach provides valuable insight, it does not consider the complex connections and relationships between variables and factors affecting green efficiency. Furthermore, this method often relies on arbitrary or subjective choices of input and output variables and the structure of the DEA model. Moreover, most DEA models assume a simple linear relationship between inputs and outputs, ignoring the mediating role of intermediary variables. While NDEA has been developed to address this limitation, determining the correct network structure remains a critical question. These limitations may lead to incorrect or contradictory results, especially when dealing with complex and multidimensional phenomena such as green efficiency.

On the other hand, ISM is a powerful method to analyze these connections but is rarely used in the context of green efficiency evaluation. Therefore, there is a clear and significant research gap in the relevant literature to develop a comprehensive framework for evaluating green efficiency by integrating ISM and DEA methods. This integration allows for a more detailed analysis of the relationships between variables and provides insights into the most important factors influencing green performance. Additionally, this study addresses another research gap by using the ISM method to determine the input, intermediate, and output variables, as well as the appropriate structure of DEA. By addressing these gaps and developing a comprehensive framework, this research contributes to the current understanding of green efficiency evaluation.

3 | Materials and Methods

The proposed NDEA model based on ISM is presented following a systematic process. *Fig. 1* illustrates the research structure of the proposed method.

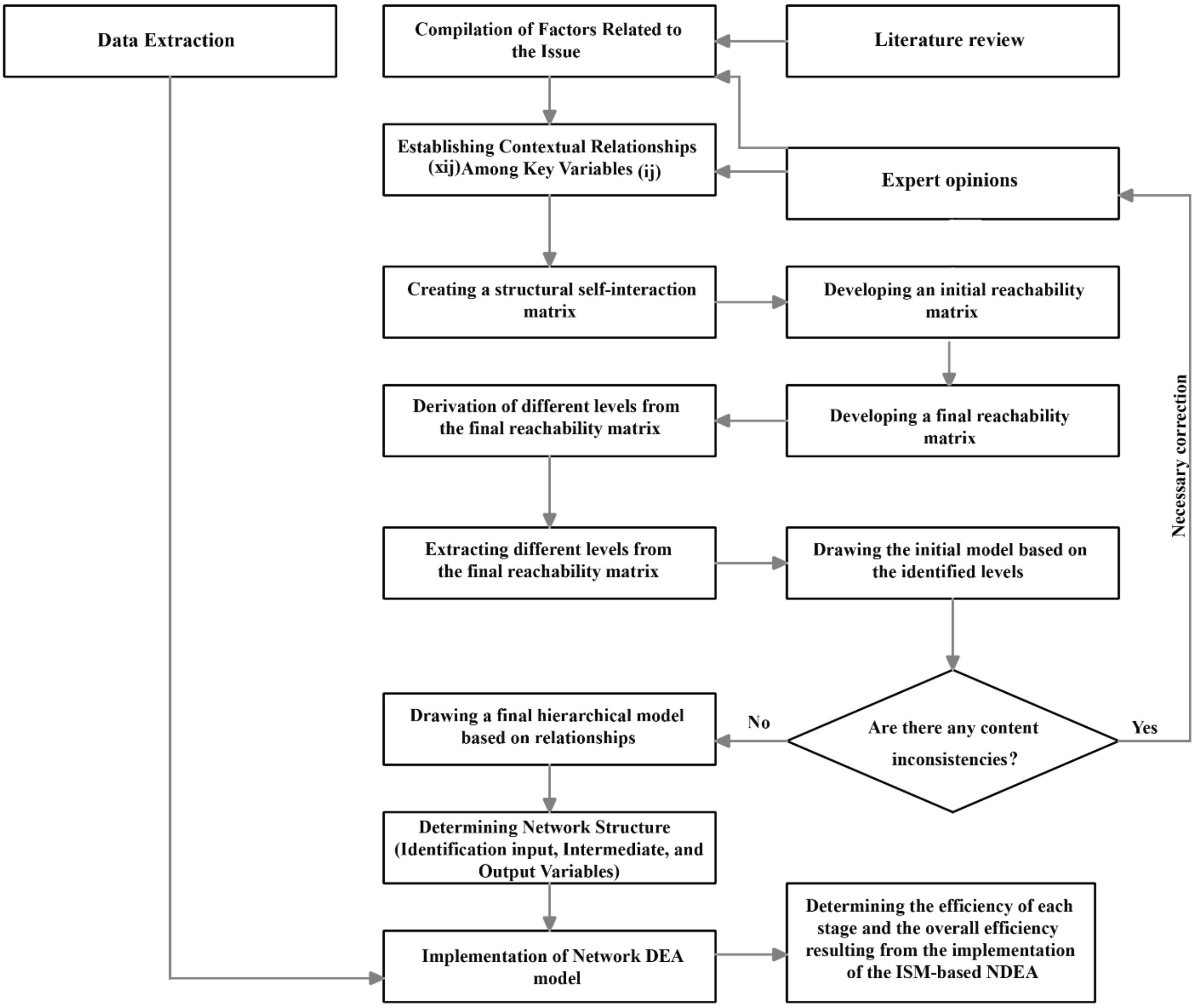

Fig. 1. Overview of the research process.

The proposed model, as illustrated in *Fig. 1*, highlights the crucial role of ISM in identifying fundamental relationships between variables, which are then used in NDEA to measure efficiency. The model is further utilized to evaluate the green efficiency scores of EU countries for validation. The required data for the study were sourced from World Bank reports and the official statistics website of the EU. The proposed model is implemented in three stages, which are thoroughly discussed in three subsections titled ISM Model Implementation, NDEA model implementation, and case study.

3.1 | ISM Model Implementation

The following are the specific implementation steps of the ISM approach:

I. Through a review of the literature and expert input, relevant variables or factors related to the issue or system under study are identified and compiled.

II. Based on the variables identified in Step 1, with the help of experts, contextual relationships are established between the variables.

III. A Structural Self-Interaction Matrix (SSIM) is developed based on expert judgments to indicate the pairwise relationships among the variables within the considered system. In this matrix, the type and direction of the relationship between two factors (i and j) are denoted by one of four symbols:

- *V: i contributes to j.*
- *A: j contributes to i.*
- *X: i and j both contribute to each other.*
- *O: i and j are not related to each other.*

IV. The initial reachability matrix is formed from the SSIM by converting qualitative opinions into binary codes, adhering to the following rules:

- *If the entry (i, j) of the SSIM is V, the (i, j) value in the reachability matrix becomes 1, and the (j, i) value becomes 0.*
- *If the entry (i, j) in the SSIM is A, the (i, j) value in the reachability matrix becomes 0, and the (j, i) value becomes 1.*
- *If the entry (i, j) of the SSIM is X, the (i, j) value in the reachability matrix becomes 1, and the (j, i) value becomes 1.*
- *If the entry (i, j) of the SSIM is O, the (i, j) value in the reachability matrix becomes 0, and the (j, i) value becomes 0.*

V. The final reachability matrix for the factors is obtained by applying the transitivity rule of the ISM approach. The reachability matrix formulated in Step 4 can be divided into distinct levels based on the reachability and antecedent sets for each factor. The reachability set for an individual factor includes the factor itself and other elements that it could help reach. Meanwhile, the antecedent set consists of the factors themselves and other factors that may aid in their achievement. In this study, the repetition leveling rule is employed for this purpose.

VI. A hierarchical model of various contributing factors is developed and formulated with the assistance of the partitioned levels.

VII. The ISM model created in Step 6 is assessed for conceptual inconsistencies and potential modifications if needed. The final hierarchical model based on relationships can be achieved by eliminating transitivity from the initial model. The findings are then utilized to interpret and draw conclusions.

Furthermore, unlike previous studies, this research marks the first instance where the ISM results are leveraged to ascertain the structure type of the DEA model and to delineate the role of variables. Consequently, when the ISM model's hierarchical structure consists of two levels, a simple DEA model is employed, whereas an NDEA model is utilized when the structure comprises more than two levels. Additionally, through the consideration of variables within each level, their respective roles as input, intermediate, or output are determined. This study effectively addresses one of the primary challenges in DEA-based performance evaluation: identifying the most suitable model type and the roles of variables within the structure.

3.2 | NDEA Model Implementation

Given that the final ISM model comprises three levels, a network structure is deemed appropriate. Since NDEA models encompass a variety of input and output types, including primary inputs, undesirable outputs, intermediate outputs, and desirable outputs [8], our study introduces a comprehensive model inspired by Cook et al. [8] that incorporates a wide range of input and output (desirable and undesirable). One of the rationales for selecting this model is its capability to derive the weight of each step. *Fig. 2* illustrates the configuration of a multi-stage process.

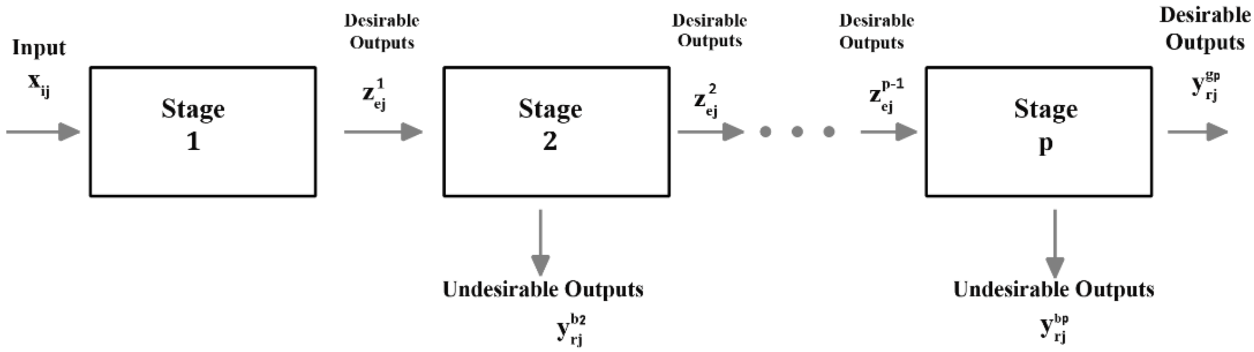

Fig. 2. Structure of a multi-stage process.

In this model, each DMU_j (j=1, …, n) are equipped with m input variables X_{ij} (i=1, …, m) in the initial stage and generates q outputs. The outputs from stage p that serve as inputs for stage p+1 is represented as Z_{ej}^{p} (e=1, …, q). The ultimate output of the unit may be classified as either desirable or undesirable. For stage p, the desirable outputs are indicated by $y_{rj}^{gp}, (r =, \dots, s)$ and the undesirable outputs are denoted by $y_{rj}^{bp}, (r = , \dots, s)$. Furthermore, the weights assigned to inputs, intermediate outputs, desirable outputs, and undesirable outputs are denoted by V_{ij}, η_{ej}^{p}, u_{rj}^{g}, u_{rj}^{b}, respectively.

In this context, as depicted in *Fig. 2*, the efficiency of each step can be reformulated as follows to accommodate the existence of undesirable outputs. It should be noted that this study employs the common method of treating undesirable outputs as inputs when modeling undesirable outputs in DEA.

$$E_1 = \frac{\sum_{e=1}^{q} \eta_{1j} z_{1j}^{1}}{\sum_{i=1}^{m} v_{1j} x_{1j}}. \tag{1}$$

$$E_2 = \frac{\sum_{e=1}^{q} \eta_{1j} z_{1j}^{2}}{\sum_{e=1}^{q} \eta_{1j} z_{1j}^{1} + \sum_{r=1}^{s} u_{1j} y_{1j}^{b2}}. \tag{2}$$

$$E_p = \frac{\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p} + \sum_{r=1}^{s} u_{rj} y_{rj}^{gp}}{\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p-1} + \sum_{r=1}^{s} u_{rj}^{b} y_{rj}^{bp}}. \tag{3}$$

The overall efficiency of the network can be expressed as the following convex linear combination:

$$E_{overall} = \sum_{p=1}^{q} W_p E_p, \text{ Where } \sum_{p=1}^{q} W_p = 1. \tag{4}$$

It is important to note that the weight of each stage signifies the significance of that stage in relation to the other stages of the network. One method to determine the weight of each stage is to consider the ratio of the input of that stage to all inputs of the network [14], as shown below:

$$W_1 = \frac{\sum_{i=1}^{m} v_{ij} x_{ij}}{\sum_{i=1}^{m} v_{ij} x_{ij} + \sum_{p=2}^{p} \left(\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p-1} + \sum_{r=1}^{s} u_{rj}^{b} y_{rj}^{bp} \right)}. \tag{5}$$

$$W_2 = \frac{\sum_{e=1}^{q} \eta_{ej} z_{ej}^{1} + \sum_{r=1}^{s} u_{rj} y_{rj}^{b2}}{\sum_{i=1}^{m} v_{ij} x_{ij} + \sum_{p=2}^{p} \left(\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p-1} + \sum_{r=1}^{s} u_{rj}^{b} y_{rj}^{bp} \right)}. \quad (6)$$

$$W_p = \frac{\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p-1}}{\sum_{i=1}^{m} v_{ij} x_{ij} + \sum_{p=2}^{p} \left(\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p-1} + \sum_{r=1}^{s} u_{rj}^{b} y_{rj}^{bp} \right)}. \quad (7)$$

Therefore, the overall efficiency of the network can be formulated as follows:

$$E_{overall} = \sum_{p=1}^{q} E_p W_p = \frac{\sum_{p=1}^{P} \left(\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p} + \sum_{r=1}^{s} u_{rj}^{g} y_{rj}^{gp} \right)}{\sum_{i=1}^{m} v_{ij} x_{ij} + \sum_{p=2}^{P} \left(\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p-1} + + \sum_{r=1}^{s} u_{rj}^{b} y_{rj}^{bp} \right)}. \quad (8)$$

Finally, the input-oriented network model with undesirable outputs can be formulated as follows (*Model (9)*)

$$\max E_{overall} = \sum_{p=1}^{P} \left(\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p} + \sum_{r=1}^{s} u_{rj}^{g} y_{rj}^{gp} \right),$$

s.t.

$$\begin{aligned}
&\sum_{i=1}^{m} v_{ij} x_{ij} + \sum_{p=2}^{p} \left(\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p-1} + \sum_{r=1}^{s} u_{rj}^{b} y_{rj}^{bp} \right) = 1, \\
&\left(\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p} \right) \le \left(\sum_{i=1}^{m} v_{ij} x_{ij} \right), \\
&\left(\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p} \right) \le \left(\sum_{i=1}^{m} v_{ij} x_{ij} \right), \qquad \text{for stage } p = 1, \\
&\left(\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p} + \sum_{r=1}^{s} u_{rj}^{g} y_{rj}^{gp} \right) \le \left(\sum_{e=1}^{q} \eta_{ej} z_{ej}^{p-1} + \sum_{r=1}^{s} u_{rj}^{b} y_{rj}^{bp} \right), \qquad \text{for stage } p > 1, \\
&v_{ij}, u_{rj}, \eta_{ej} \ge 0.
\end{aligned} \quad (9)$$

The objective function of Model 9 quantifies the overall efficiency of the network, assigning a score on a scale from 0 to 1. The DMU is considered efficient if this score is 1. The first constraint of this model ensures that the sum of all inputs equals 1. The second constraint ensures that the output of the first stage is less than or equal to the inputs of that stage, while the third constraint ensures that the output of each stage, denoted as p, remains smaller than the inputs of that stage. The efficiency of the components of the network is given by

$$E_1 = \frac{\sum_{e=1}^{q} \eta_{ej}^{*} z_{ej}^{1}}{\sum_{i=1}^{m} v_{ij}^{*} x_{ij}}. \quad (10)$$

$$E_p = \frac{\sum_{p=2}^{P} \left(\sum_{r=1}^{s} u_{rj}^{*} y_{rj}^{gp} + \sum_{e=1}^{q} \eta_{ej}^{*} z_{ej}^{p} \right)}{\sum_{p=2}^{P} \left(\sum_{e=1}^{q} \eta_{ej}^{*} z_{ej}^{p-1} + \sum_{r=1}^{s} u_{rj}^{*} y_{rj}^{bp} \right)}, \quad (11)$$

where E_1 and E_p denote the efficiency of the first stage and the p-th stage, and * denotes the optimal weight for inputs and outputs.

3.3 | Case Study

As mentioned in the preceding section, implementing the innovative ISM-based Network DEA to measure the efficiency of 27 EU countries required extracting the total factors of green production development. This step was accomplished through a comprehensive review of existing literature and interviews with experts in the field. By gathering insights from these sources, the necessary factors were identified and compiled for further analysis and evaluation. Subsequently, content analysis was employed to identify and remove any redundant actions from the initial list. Additionally, actions that fell under the same category were combined for clarity. An expert committee consisting of 12 members was formed to determine the importance of these measures. These experts were provided with a list of the identified effective measures in the field under investigation. The experts evaluated the importance of each measure both in person and electronically. In the analysis of the survey responses, it was found that the average answers to all the questions fell within the range of agreement, indicating a consensus among the experts. Consequently, none of the measures were excluded from the final list. *Table 3* presents the obtained factors for the development of green production, as derived from the relevant literature and based on the opinions of the experts.

Table 3. Factors of green production development and their symbols.

Factor	Symbol
Energy consumption	C_1
Water consumption	C_2
Labor	C_3
Capital	C_4
GHG emission	C_5
GDP	C_6
Green technology	C_7
Raw materials	C_8

Afterward, a questionnaire designed to assess the textual relationship between the various factors was provided to the expert committee members. Following their completion of the questionnaires, the identified relationships were evaluated based on their frequency, and collaborative brainstorming sessions were held with the expert committee members. Through these discussions and analyses, the final SSIM was formed (*Table 4*).

Table 4. SSIM.

Factor	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	-	X	X	X	V	V	V	X
C_2		-	X	X	V	V	V	X
C_3			-	X	V	V	V	X
C_4				-	V	V	V	X
C_5					-	A	X	A
C_6						-	V	A
C_7							-	A
C_8								-

The initial reachability matrix was established by converting the symbols within the SSIM into binary values of zero or one, following the rules outlined in the literature review section (*Table 5*).

Table 5. Initial reachability matrix.

Factors	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	1	1	1	1	1	1	1	1
C_2	1	1	1	1	1	1	1	1
C_3	1	1	1	1	1	1	1	1
C_4	1	1	1	1	1	1	1	1
C_5	0	0	0	0	1	0	1	0
C_6	0	0	0	0	1	1	1	0
C_7	0	0	0	0	1	0	1	0
C_8	1	1	1	1	1	1	1	1

Subsequently, the final reachability matrix was obtained by removing transitivity links as described in Step 4 of the ISM methodology, and it is displayed in *Table 6*. This final reachability matrix comprises entries derived from pairwise comparisons as well as others obtained from inference.

Table 6. Final reachability matrix.

Factors	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	Driving Power
C_1	1	1	1	1	1	1	1	1	8
C_2	1	1	1	1	1	1	1	1	8
C_3	1	1	1	1	1	1	1	1	8
C_4	1	1	1	1	1	1	1	1	8
C_5	0	0	0	0	1	0	1	0	2
C_6	0	0	0	0	1	1	1	0	3
C_7	0	0	0	0	1	0	1	0	2
C_8	1	1	1	1	1	1	1	1	8
Dependence	5	5	5	5	8	6	8	5	

At this stage, the final reachability matrix was utilized to derive the reachability and antecedent sets for each variable. By examining the intersection of these sets, the levels of different factors were ascertained. Factors sharing the same reachability and intersection sets were positioned at the top level in the ISM hierarchy. Once the top-level factor was identified, it was excluded from further consideration. The process was then iterated to identify the factors at the subsequent level. This iterative approach was continued until the level of each factor was determined, progressively unveiling the hierarchical structure of the factors. The reachability, antecedent, and intersection sets and the levels of the eight factors in this study are detailed in *Table 7*.

Table 7. Level partitioning results.

First Iteration **Factor**	**Reachability Set**	**Antecedent Set**	**Intersection Set**	**Level**
Energy consumption	1-2-3-4-5-6-7-8	1-2-3-4-8	1-2-3-4-6-8	
Water consumption	1-2-3-4-5-6-7-8	1-2-3-4-8	1-2-3-4-6-8	
Labor	1-2-3-4-5-6-7-8	1-2-3-4-8	1-2-3-4-6-8	
Capital	1-2-3-4-5-6-7-8	1-2-3-4-8	1-2-3-4-6-8	
GHG emission	5-7	1-2-3-4-5-6-7-8	5-7	First level
GDP	5-6-7	1-2-3-4-6-8	6	
Green technology	5-7	1-2-3-4-5-6-7-8	5-7	First level
Raw materials	1-2-3-4-5-6-7-8	1-2-3-4-8	1-2-3-4-6-8	
Second Iteration				
Energy consumption	1-2-3-4-6-7-8	1-2-3-4-8	1-2-3-4-8	
Water consumption	1-2-3-4-6-7-8	1-2-3-4-8	1-2-3-4-8	
Labor	1-2-3-4-6-7-8	1-2-3-4-8	1-2-3-4-8	
Capital	1-2-3-4-6-7-8	1-2-3-4-8	1-2-3-4-8	
GDP	6	1-2-3-4-6-7-8	6	Second. level
Raw materials	1-2-3-4-6-7-8	1-2-3-4-8	1-2-3-4-8	

Table 7. Continued.

Third Iteration				
Energy consumption	1-2-3-4-8	1-2-3-4-8	1-2-3-4-8	Third level
Water consumption	1-2-3-4-8	1-2-3-4-8	1-2-3-4-8	Third level
Labor	1-2-3-4-8	1-2-3-4-8	1-2-3-4-8	Third level
Capital	1-2-3-4-8	1-2-3-4-8	1-2-3-4-8	Third level
Raw materials	1-2-3-4-8	1-2-3-4-8	1-2-3-4-8	Third level

The final interpretive structural model was formed by removing transitivity, as shown in *Fig. 3*. The resulting model obtained in this study consists of three levels, showcasing the hierarchical relationships among the factors.

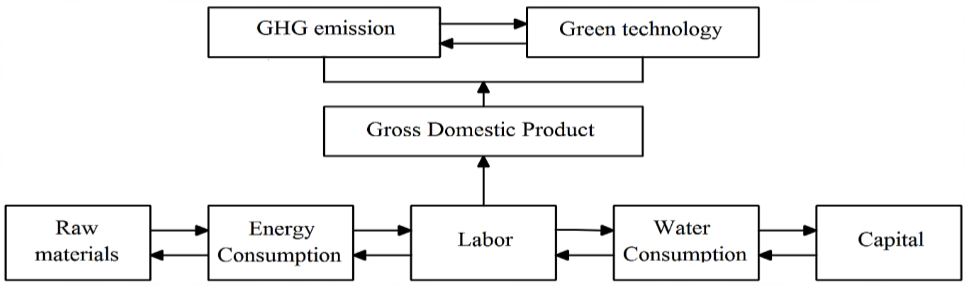

Fig. 3. ISM-based model of the factors influencing green production development.

Given the aim of this model's implementation to discern the most appropriate type of DEA model and the role of variables in the model's framework, the utilization of the MIC-MAC figure is eschewed. Based on the results obtained from the ISM model, the roles of the variables and the overall network structure were determined. In this study, a two-stage structure has been established, with the first stage representing economic efficiency and the second stage representing environmental efficiency. In this context, the labor force, capital, energy consumption, water consumption, and raw materials were identified as inputs in the initial stage, while the GDP served as an intermediate variable. The factors of green technology and greenhouse gas emissions were designated as outputs in the subsequent stage. Specifically, for green technology, the advanced technology export index was utilized, while for greenhouse gases, indicators for CO2 gas emissions and the capacity to absorb greenhouse gases were employed. These were considered as the final undesirable and desirable outputs by the environment, respectively. The structure is illustrated in *Fig. 4*.

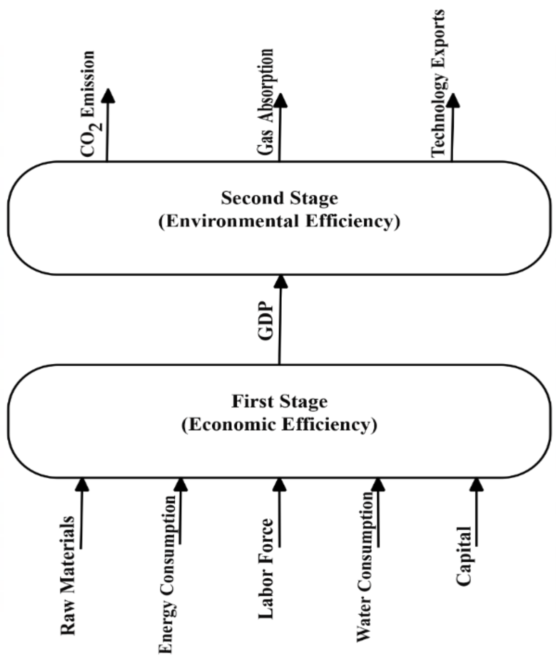

Fig. 4. The structure of the countries under study.

To access country-specific data for EU countries, information was extracted from worldbank.org and Eurostat. The dataset used in this study pertains to 2018. It is important to note that the mathematical models and theorems presented are grounded in sound principles of mathematics and operations research. Consequently, the temporal domain does not limit the application of the approaches outlined in this study. In other words, the data is time-independent and is solely presented to elucidate the functionality of the models and to clarify the operational application of the approaches. The indicators, along with their sustainability dimensions, are detailed in *Table 8*.

Table 8. Data used in efficiency evaluation.

Stage	Indicator	Sustainability Dimension	Notation	Mean	Max	Min	
First stage (economic efficiency)	Energy consumption	Economic	X1	40.14	50.2043	0.66	215.37
	Water consumption	Economic	X_2	9333.66	17834.45	31.02	87942.78
	Labor	Economic	X_3	8.89	11.4228	0.227	43.423
	Capital	Economic	X_4	3326.75	4738.21	76.37	17198.61
	Raw materials	Economic	X_5	320.88	541.55	3.403	2734.176
Intermediate	GDP	Economic	z_1^1	685.46	1014.46	13.75	3939.277
Second stage (environmental efficiency)	Technology exports	Economic	y_1^{g2}	27.56	45.129	0.096	210.082
	Gas absorption	environment	y_2^{g2}	16342.28	14607.37	0	48587
	CO2 emission	environment	y_1^{b2}	141178.77	189778.9	2190.45	831437

Given the fundamental tenet of DEA that efficiency assessment hinges on the intricate relationships between DEA components, namely inputs, and outputs, we conducted a thorough examination of the correlation between these variables. *Tables 9* and *10* present a comprehensive summary of the correlations between input and output factors within both the economic and environmental performance domains. It is important to note that a strong correlation between inputs and outputs is indicative of a higher efficiency score [46].

Table 9. Correlation between the inputs and outputs of the first stage.

		Inputs Energy Consumption	Water Consumption	Labor	Capital	Raw Materials	Output GDP
Inputs	Energy consumption	1.0000	0.4450	0.9850	0.9806	0.6232	0.9858
	Water consumption	-	1.0000	0.5057	0.4243	0.0340	0.4241
	Labor	-	-	1.0000	0.6532	0.6767	0.9695
	Capital	-	-	-	1.0000	0.0343	0.9973
	Raw materials	-	-	-	-	1.000	0.6368
Output	GDP	-	-	-	-	-	1.0000

Table 9 reveals a notable average correlation between inputs and outputs within the economic efficiency stage, suggesting a high average efficiency level in this phase. It is worth noting that a DMU may not necessarily require more inputs to generate additional outputs, especially when alternative inputs are utilized, potentially resulting in a negative correlation between inputs and outputs.

Table 10. Correlation between the inputs and outputs of the second stage.

		Input GDP	Output Technology Exports	CO2 Emission	Gas Absorption
Input	GDP	1.0000	0.8771	0.5618	0.5161
Outputs	Technology exports	-	1.0000	-0.0423	0.3549
	CO2 emission	-	-	1.0000	-0.0994
	Gas absorption	-	-	-	1.0000

In *Table 10,* a significant correlation is observed between input and output variables in the environmental efficiency stage, indicating a relatively high average efficiency level in this stage as well. *Table* 11 presents the efficiency values of the first and second stages, representing economic and environmental efficiency, respectively. These values were determined through the application of *Eqs. (10)* and *(11)*. Subsequently, the overall efficiency values for 27 EU countries were computed using *Model (9)*.

Table 11. Results of the models.

Country	Weight in the First Stage	Efficiency in the First Stage	Weight in the Second Stage	Efficiency in the Second Stage	Overall Efficiency
Austria	0.5070	0.9721	0.4929	0.2997	0.6406
Belgium	0.5071	0.9717	0.4928	0.4964	0.7375
Bulgaria	0.5733	0.7439	0.4266	0.7475	0.7454
Croatia	0.5457	0.8323	0.4542	0.5446	0.7016
Cyprus	0.5131	0.9486	0.4868	1.0000	0.9736
Czechia	0.5293	0.8890	0.4706	1.0000	0.9412
Denmark	0.5000	1.0000	0.5000	0.1985	0.5992
France	0.5000	1.0000	0.5000	0.2924	0.6462
Finland	0.5347	0.8699	0.4652	0.2118	0.5670
Estonia	0.5608	0.7829	0.4391	1.0000	0.8782
Greece	0.5581	0.7915	0.4418	0.1145	0.4924
Germany	0.5000	1.0000	0.5000	0.3775	0.6887
Hungary	0.5214	0.9179	0.4785	0.8666	0.8933
Ireland	0.5000	0. 6706	0.5000	1.0000	0.8253
Italy	0.5000	0.9981	0.5000	0.1344	0.5667
Latvia	0.5000	0.9540	0.5000	1.0000	0.9770
Lithuania	0.5633	0.7751	0.4366	0.7253	0.7534
Luxembourg	0.5000	0.4349	0.5000	1.0000	0.7174
Netherlands	0.5000	1.0000	0.5000	0.6320	0.8186
Poland	0.5000	0.8059	0.5000	0.2424	0.5241
Portugal	0.5282	0.8930	0.4717	0.5343	0.7238
Romania	0.5243	0.9071	0.4756	0.2952	0.6160
Slovakia	0.5015	0.9936	0.4984	0.9394	0.9666
Slovenia	0.5289	0.8905	0.4710	0.6754	0.7891
Spain	0.5000	0.5405	0.5000	0.0811	0.3108
Sweden	0.5063	0.9747	0.4936	0.3096	0.6464
United Kingdom	0.5000	1.0000	0.5000	0.2090	0.6045
Average	-	0.8802	-	0.5528	0.7164

4 | Sensitivity Analysis

In this section, the competitive advantage of economic DMUs is identified by measuring the significance of input indicators and their impact on GDP. This objective was achieved through sensitivity analysis, systematically removing each variable, and running the model with the remaining variables to assess their individual effects on the GDP of each country. The outcomes of this sensitivity analysis are detailed in *Table 12*.

Table 12. Results of sensitivity analysis.

Country	Efficiency Score after Removing the Input					Ranking after Removing the Input					Main Ranking
	Energy Consumption	Water Consumption	Labor	Capital	Raw Materials	Energy Consumption	Water Consumption	Labor	Capital	Raw Materials	
Austria	0.9716	0.9171	0.9721	0.6732	0.9721	7	10	3	10	4	5
Belgium	0.9717	0.9660	0.9717	0.8593	0.9254	6	6	4	4	6	6
Bulgaria	0.7439	0.7439	0.7439	0.2288	0.7439	24	24	20	23	19	20
Croatia	0.8323	0.8322	0.8323	0.4320	0.8323	19	19	15	16	14	15
Cyprus	0.9486	0.9486	0.9486	0.6885	0.8931	10	8	8	8	9	8
Czechia	0.8890	0.8890	0.8890	0.3191	0.8890	16	15	13	18	11	13
Denmark	0.8846	0.9097	1.0000	1.0000	1.0000	17	11	1	1	1	1
France	0.9810	0.9786	0.9563	1.0000	1.0000	5	4	5	1	1	1
Finland	0.8699	0.8699	0.8559	0.4765	0.8699	18	18	14	14	13	14
Estonia	0.7829	0.7829	0.7829	0.2788	0.7829	21	22	18	22	16	18
Greece	0.7620	0.7915	0.7915	0.6767	0.7685	23	21	17	9	18	17
Germany	1.0000	1.0000	1.0000	0.8202	1.0000	1	1	1	6	1	1
Hungary	0.9179	0.8743	0.9179	0.4526	0.9165	11	17	9	15	7	9
Ireland	0.9073	1.0000	1.0000	1.0000	1.0000	12	1	1	1	1	21
Italy	0.9875	0.9653	0.9563	0.9494	0.9363	4	7	6	3	5	2
Latvia	1.0000	0.9839	1.0000	0.3867	1.0000	1	3	1	17	1	7
Lithuania	0.7751	0.7751	0.7751	0.2956	0.7751	22	23	19	20	17	19
Luxembourg	1.0000	1.0000	1.0000	1.0000	1.0000	1	1	1	1	1	23
Netherlands	0.9608	0.9463	1.0000	1.0000	1.0000	9	9	1	1	1	16
Poland	0.8059	0.8153	0.7963	0.2838	0.8059	20	20	16	21	15	11
Portugal	0.8930	0.8930	0.8930	0.5763	0.8930	14	14	11	13	10	10
Romania	0.9071	0.9071	0.9071	0.3105	0.9071	13	12	10	19	8	3
Slovakia	0.9936	0.8954	0.9936	0.5860	0.9932	2	13	2	11	2	12
Slovenia	0.8905	0.8785	0.8905	0.5826	0.8807	15	16	12	12	12	22
Spain	1.0000	1.0000	1.0000	0.8503	1.0000	1	1	1	5	1	4
Sweden	0.9644	0.9747	0.9495	0.6948	0.9747	8	5	7	7	3	1
United Kingdom	0.9916	0.9863	1.0000	0.9675	1.0000	3	2	1	2	1	5

The results of the sensitivity analysis offer valuable insights and information, which will be elaborated on in the following section.

5 | Finding

There are several significant findings and managerial implications stemming from our study. Our research showcases the effectiveness of heuristic approaches grounded in ISM for organizing variables and understanding their impacts on green efficiency. Through ISM, we successfully pinpointed the pivotal variables influencing green efficiency. This structured methodology equips policymakers and businesses with

a holistic understanding of the factors influencing green performance, facilitating targeted policy implementation and resource allocation. Moreover, our examination of green efficiency across EU countries has uncovered notable disparities, underscoring the necessity for enhancing sustainable practices and environmental performance throughout the region. Similar results were found in the studies by Halkos and Petrou [47] and Moutinho et al. [48], highlighting the inequality and the urgent need to enhance sustainable practices in the developing countries of Europe. By integrating our framework, policymakers can pinpoint areas needing improvement, enact customized policies, and monitor progress over time. This strategic approach not only advances the EU's sustainability objectives but also propels the shift towards a more sustainable economy. Furthermore, our framework enables the identification of competitive advantages for each DMU within EU countries. This information can be valuable for businesses, as it allows them to understand their relative position in terms of green efficiency compared to their competitors. Armed with this knowledge, companies can devise strategies to bolster their environmental performance, gain a competitive edge, and cater to the escalating demand for sustainable products and services.

Delving into the efficiency of DMUs across economic and environmental dimensions has yielded intriguing insights. This discovery underscores the intricate balance required between economic and environmental efficiencies. It suggests that while certain countries may excel in one aspect, they might lag in another, emphasizing the necessity for comprehensive strategies and policies addressing both economic and environmental considerations. Furthermore, the identification of countries achieving peak efficiency in each realm furnishes policymakers with invaluable guidance for informed decision-making.

For example, the first-stage countries (Denmark, France, Germany, the Netherlands, and the United Kingdom) demonstrate effective resource utilization and economic efficiency. Policymakers in other countries can learn from these approaches and policies to improve their economic performance. Similarly, the second-stage countries (Cyprus, Czechia, Estonia, Ireland, and Luxembourg) showcase successful environmental performance. Policymakers in other countries can study these practices and policies to enhance environmental efficiency in their own countries. These findings highlight the importance of knowledge sharing and collaboration among countries to promote sustainable practices and improve overall performance. Additionally, these findings signify that there is room for improvement for countries that did not achieve maximum efficiency in either stage. By addressing areas in need of improvement, these countries can work towards achieving balanced and sustainable development.

The ability to draw such conclusions is a distinctive feature of the NDEA used in our study, which is not present in classical DEA models. The average efficiency score across all countries was 0.7164, indicating an average level of efficiency. Specifically, the average economic efficiency score was 0.8802, reflecting relatively strong performance in terms of economic efficiency. In contrast, the average environmental efficiency score was 0.5528, indicating poor efficiency in this area. A significant portion of this inefficiency can be attributed to undesirable outputs, particularly CO2 emissions. It is worth noting that the weight of each stage (economic, environmental) was automatically determined by the model based on the input variables of that stage. It's important to highlight that altering the weight of each stage leads to a change in the total efficiency score of each country, and these weights can also be determined based on the country's economic policies. Additionally, our model goes beyond simple efficiency assessment by utilizing the ISM approach to identify and analyze the relationships between variables. This allows us to create a network structure that provides a deeper understanding of the interconnections and dependencies between variables. In comparison to traditional subjective structuring methods, our sophisticated approach enables a more objective and insightful analysis. The sensitivity analysis conclusion underscores the diverse impacts of different resource utilization on the efficiency and rankings of countries. Particularly, the exclusion of the energy consumption variable significantly influenced the ranking of certain countries, such as Latvia, Luxembourg, the Netherlands, Slovakia, Slovenia, and Spain, indicating their suboptimal performance in managing energy sources. Conversely, Denmark, France, Poland, Portugal, Romania, and Sweden were highly sensitive to energy sources, as their rankings experienced a considerable decline when the energy variable was removed. This

suggests that these countries have effectively utilized energy inputs compared to other nations, potentially providing them with a competitive advantage.

Similarly, the exclusion of the water consumption variable led to increased efficiency scores and rankings for countries like Ireland, Latvia, Luxembourg, and the Netherlands, implying a more efficient use of water resources in comparison to other countries. This indicates that these nations have successfully optimized their utilization of water resources. Conversely, the labor force variable did not significantly impact the efficiency scores and rankings of most countries, suggesting that labor may not serve as a significant competitive advantage for these nations. However, when considering the labor force variable, some countries, including Ireland, Latvia, Luxembourg, the Netherlands, and Slovakia, exhibited higher sensitivity, as their efficiency scores and rankings notably changed after its exclusion.

Moreover, the removal of the capital source variable revealed it to be the most influential variable after energy. Notably, the efficiency scores and rankings of the majority of countries experienced significant shifts following the elimination of this variable. For instance, Ireland and Greece demonstrated an improvement in ranking and performance, indicating a suboptimal utilization of capital resources compared to other countries. Conversely, countries like Austria, the Czech Republic, Germany, and Latvia experienced a decline in efficiency scores and rankings, showcasing their effective utilization of capital resources. Furthermore, the exclusion of the raw material variable showed that, with the exception of seven countries, most nations displayed limited sensitivity to this variable, suggesting that it had a minimal impact on efficiency and rankings. Notably, Germany emerged as the only country with minimal changes after removing these indicators, indicating its exceptional performance and optimal use of resources compared to other countries. This suggests that Germany could potentially serve as a model for resource utilization practices for other nations.

6 | Conclusion

n this study, we introduced an innovative integrated framework aimed at overcoming limitations in previous methods of evaluating green efficiency. Our hybrid approach combines ISM and NDEA techniques. Moreover, inspired by Cook et al.'s model [8], we presented a model for effectively adapting to undesirable variables. The key contributions and advantages of our study, compared to earlier research, lie in its ability to consider the interplay between variables in determining the number of stages and integrating input, intermediate, and output variables in DEA models. This systematic approach eliminates the need for subjective adjustments, making it particularly advantageous for the development of DEA models in situations with numerous variables. The implementation of our method has significant implications for policymakers and enriches the literature on sustainable development and efficiency evaluation. However, future research could improve and expand the application of this systematic framework. Specifically, our integrated framework is tailored to address the limitations of existing methods for evaluating green efficiency and can be extended to various regions and sectors, allowing for comprehensive comparison and benchmarking on a larger scale. This enables valuable insights and promotes the identification of best practices across different fields. Additionally, the framework is flexible enough to incorporate additional variables and indicators, providing a more holistic view of green performance. By considering a broader range of factors, researchers can attain a more precise understanding of sustainability and improve the accuracy of their assessments. Efforts can also be directed towards integrating quantitative and qualitative data sources to enhance the accuracy and depth of analysis.

Utilizing fuzzy logic and uncertainty space within ISM can assist in determining the levels and structure of the DEA model. Additionally, a suggestion for future research would be to present a DEA model considering the assumption of Variable Returns to Scale (VRS) to achieve more realistic results. Moreover, the current research, initially proposed for a series structure, has the potential for development in parallel or hybrid network structures. Overall, this research did not encounter significant limitations. However, challenges arose from the significant number of experts not responding to the designed questionnaire. Additionally, due to the

unavailability of necessary information about Iran, the study focused on examining the proposed model within EU countries.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data are included in the text.

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